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SHEILA

SUPPORTING HIGHER EDUCATION
TO INTEGRATE LEARNING ANALYTICS

RESEARCH REPORT NOVEMBER 2018

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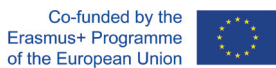


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1. Executive summary

Learning analytics promises to enhance learning and teaching by providing insights into learning engagement and progression, thereby informing teaching and learning decisions.

While interest in learning analytics (LA) has grown rapidly among higher education institutions (HEIs), the maturity levels of HEIs in terms of being 'student data informed' are only at early stages. To assist European higher education institutions to become more mature users and custodians of digital data collected from students during their online learning activities, the SHEILA (Supporting Higher Education to Integrate Learning Analytics) project, co-co-funded by the European Commission via the Erasmus+ program, aimed to build a policy development framework that supports systematic, sustainable and responsible adoption of LA at an institutional level. To this end, a series of research activities have taken place since January 2016 until September 2018 to investigate the state of the art in terms of LA adoption in Europe, drivers for adoption, challenges, and successes to date.

The study has engaged a wide range of stakeholders, including institutional leaders, teaching staff, students, and LA experts, using surveys, interviews, focus groups, and a group concept mapping activity. Based on the results of these research activities and the Rapid Outcome Mapping Approach (ROMA) [9, 21], we developed a policy framework, addressed as the SHEILA framework¹ hereafter, to guide individual institutions to develop a comprehensive policy that speaks to the needs of their

particular contexts and stakeholders therein. The framework has been tested and validated by 200 external stakeholders, primarily comprising institutional leaders, policy makers, LA researchers, teaching staff, support professionals, and students, between March and November 2018. The framework has also informed the policy and strategy processes in four European HEIs, including the University of Edinburgh, Universidad Carlos III de Madrid, the Open University of the Netherlands, and Tallinn University. For example, the "Policy and Procedures for Developing and Managing Learning Analytics Activities"² developed at the University of Edinburgh is an exemplar followed by several HEIs now. A number of materials produced by the SHEILA project are now open resources for HEIs to start the process of engaging key stakeholders and formulating a policy for LA. These materials include the SHEILA framework, the manual and handout of the SHEILA framework, survey and focus group protocols³, and the SHEILA MOOC⁴.

¹<http://sheilaproject.eu/sheila-framework/>

²http://bit.ly/LA_policy_UoE

³<http://sheilaproject.eu/sheila-framework/>

⁴<http://bit.ly/SHEILAMOOC>

In addition to the SHEILA framework, as a primary intellectual output, the study highlights six key findings:

1. The adoption of LA among European HEIs was in early phases with unclear strategies and lacking monitoring frameworks.
2. Institutional leaders were particularly interested in adopting LA to improve institutional performance, whereas teachers were keen to use it to enhance curriculum design, and students were eager to receive personalised support.
3. Ethics and privacy were considered the most important elements to include in a LA policy, and a key factor influencing student buy-in.
4. Both teachers and students expressed an expectation of LA to enhance student agency and self-regulated learning skills rather than hampering them through a spoon-feeding or datafication approach.
5. Analytics expertise, data culture, staff buy-in, and technological infrastructure are four key dimensions of institutional capacity to enable successful adoption of LA.
6. To close the feedback loop effectively, it is crucial to involve pedagogical expertise and equip key users with reflective skills to interpret data and turn it into constructive actions.

In light of these findings, we recommend a dialogical approach to dealing with the social and cultural challenges associated with LA, so as to move towards systematic adoption under a shared vision across the institution. Moreover, we believe that HEIs have the onus to ensure that LA is used effectively and ethically. To this end, a policy agenda ought to be in place to meet the needs of every stakeholder involved in the implementation of LA.

2. Context and rationale

Learning analytics has emerged as an interdisciplinary field that brings together research and practice in education, psychology, and data science.

Learning analytics collects, measures, analyses, and reports data about learners for the purpose of leveraging human decisions to improve learning and the environments where it occurs [7]. Siemens [12] argues that data captured while students are engaged in authentic learning can provide great insights into the social and pedagogical dimensions of learner performance. The analysis of such data can advance our understanding of the learning process and in turn informs learning design and strategy. In the 2018 NMC Horizon Report Preview [4], LA is mentioned as an important educational technology to support adaptive learning. It is believed that adaptive learning technologies can potentially provide a solution to the ‘iron triangle’ of educational challenges, including the increasing cost of higher education, the challenge of providing access to new generations of students; and the need to maintain and improve educational quality. LA can be used to create flexible pathways to learning success, target at-risk student populations, and assess factors that affect completion and student success.

Despite the increasing interest among higher education institutions (HEIs) in employing LA to increase the quality of teaching and learning, there are often barriers that prevent data from being used systematically and effectively. For example, data quality, ownership, access, organisational culture, and expertise available to implement LA are

prevalent issues that need to be addressed [1]. Siemens and colleagues [13] contend that LA includes technical, cultural and social aspects, and as such its associated challenges are not limited to technical problems only. Therefore, an institutionally wide strategy (a plan of action to achieve goals and objectives) will be needed to build analytics mindsets, capabilities, and capacity. However, research has found that although funding opportunities for LA research and activities have increased, there is still a lack of systematic and large-scale implementations of LA in higher education [5, 16]. In order to establish analytics sustainability, it is imperative that HEIs align the adoption of LA with their institutional vision and goals [13]. Moreover, HEIs need a strategic planning process to overcome institutional resistance to innovation and change [8]. Further, Prinsloo and Slade [11] point out that the harvesting, use, and dissemination of data requires an institutional policy (a set of guidelines and principles) that aligns with national and international legislative frameworks, so as to ensure an enabling environment for LA. It is important to establish principles to guide stakeholders and encourage ethical use of data within an educational system where power is unequally distributed among different stakeholders.

In light of the need for a sound policy and a strategic planning process that is tailored to meet individual institutions' unique contexts and ensures a responsible and effective use of student data for LA, the SHEILA (Supporting Higher Education to Integrate Learning Analytics) project⁵ was launched in 2016 with the goal of assisting HEIs to become mature users and custodians of digital data concerning their students. With evidence collected from direct engagement with stakeholders to understand their perceptions, expectations and concerns, a framework (addressed as the SHEILA framework⁶ hereafter) has been developed to assist with policy and strategy formation processes for institutional adoption of LA. Existing models that seek to guide the adoption of LA in higher education include Jisc's "Code of Practice for Learning Analytics" [6] and the Open University in the UK's "Policy on Ethical use of Student Data for Learning Analytics" [10]. However, these ethical and privacy guidelines may not always apply to every institution's unique context. The SHEILA framework collates the adoption experiences of LA from a wide array of HEIs in Europe and it serves as a resource for the preparation of an institutional policy or strategy for LA. The SHEILA framework was built using the RAPID Outcome Mapping Approach (ROMA) [8]. Although the literature has suggested that the ROMA model is an effective tool to support systematic adoption of LA in HEIs [5, 8], there has been limited work that purposely involved

different stakeholder groups to validate the feasibility of this tool for LA strategy and policy development. The contribution of our work is to bridge this gap and adapt the use of the ROMA model to address challenges recognised in the literature and raised by different stakeholder groups.

To this end, the SHEILA project intended to answer the following research questions:

1. What is the state of the art in terms of LA adoption among European HEIs?
2. What are the key drivers for LA from the perspectives of institutional leaders, teaching staff, and students?
3. What are the key challenges for LA from the perspectives of institutional leaders, teaching staff, and students?
4. How can we move towards systematic adoption of LA in higher education?

We adopted a mixed methods approach to research using surveys, interviews, focus groups, and a group concept mapping. Prior to these main research activities, we carried out a systematic literature review on relevant empirical studies and LA policies to map out the state of LA in higher education and identify emerging challenges. In the next section, we explain these activities in detail.

⁵<http://sheilaproject.eu/>

⁶<http://sheilaproject.eu/sheila-framework/>

3. Methodology

In this section, we first explain the methods adopted for a systematic literature review undertaken in the early phase of the project. Then we illustrate the approaches taken to engage key stakeholders of LA, including institutional leaders, teaching staff, students, and LA experts, and the methods used to analyse the data.

3.1 LITERATURE REVIEW

The search of relevant literature was carried out in four stages between June and July 2016. The first stage involved key word searches (“learning analytics” AND (“policy” OR “policies”)) on various databases and journals that were known for substantial collections of studies in the fields of LA, social sciences and computer science. The main topics considered included ethics and privacy, policies, institutional strategies, institutional readiness, and institutional capacities. Table 1 gives an overview of the sources that we have consulted and Table 2 explains the selection criteria of topics and

publication types that we used to filter the search results.

The bibliographical research did not discriminate between the publication years, as to our knowledge the field only emerged in 2010 [5]. It finished in July 2016 and rendered 71 pieces of literature, among which 25 were empirical studies, 38 were desk studies, and eight were policies for LA. We reviewed the eight policies and 23 empirical studies, after further filtering out two studies based on the degree of relevance to our research interest.

Table 1. Sources of the bibliographical research

Databases	SCOPUS, Wiley Online Library, ERIC, ACM, IEEE
Journals	Journal of Learning Analytics, Journal of Computer Assisted Learning, Journal of Educational Technology & Society, American Behavioural Scientist, Journal of Educational Technology & Society, The Information Society, Computers & Education
Proceedings	International Conference on Learning Analytics & Knowledge (LAK)
Organisational databases	LACE publications, EDUCAUSE library

Table 2. Filter criteria for the bibliographical research

	Topics	Types of publications
Included	Ethics and privacy, policies, institutional strategies, institutional readiness, institutional capacities, learning analytics, academic analytics	Research reports, conference proceedings, journal articles, book chapters, policy documents, all years of publication, English language
Excluded	Affordances of learning analytics models and tools, interventions on class or individual levels, approaches to analytics, studies not based in higher education institutions	PowerPoint presentations, blog articles, news articles, workshops

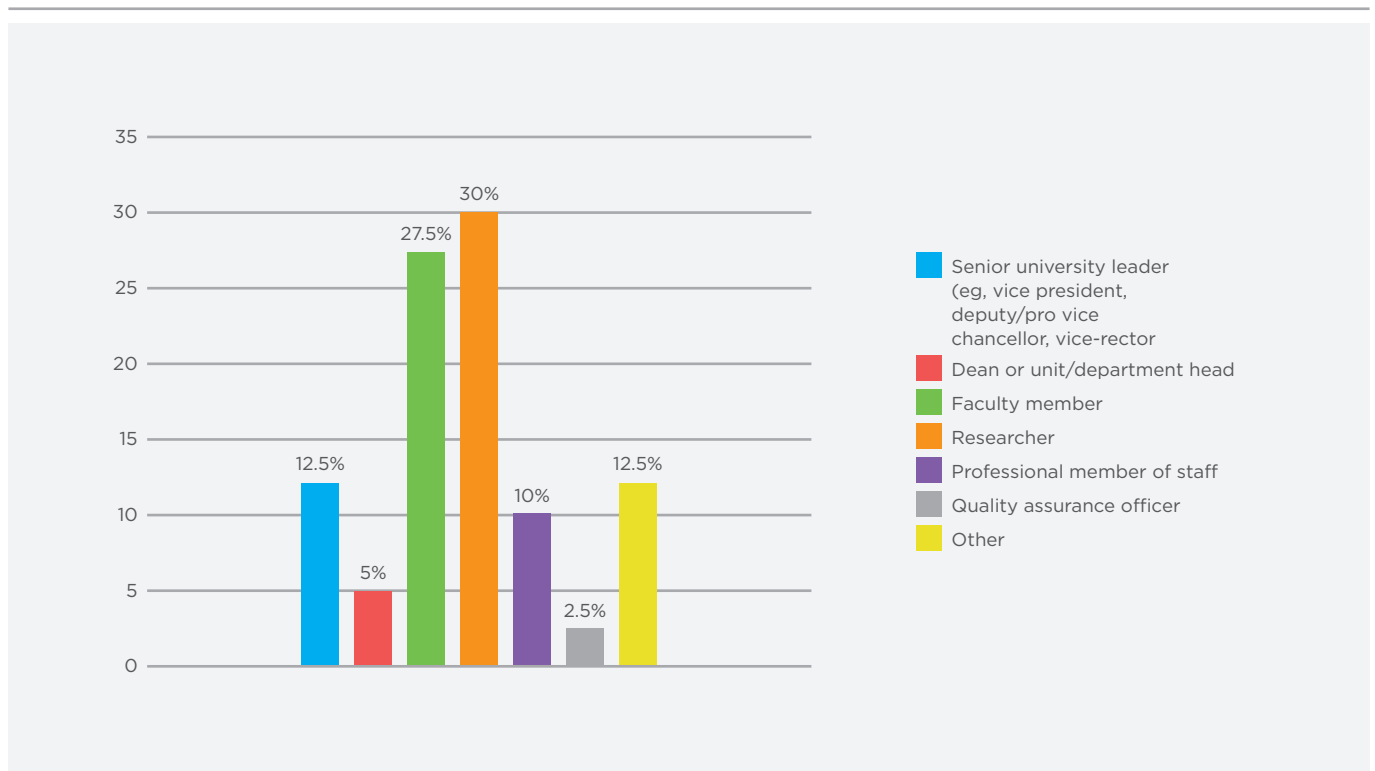
3.2 LA EXPERTS – GROUP CONCEPT MAPPING

The group concept mapping (GCM) activity⁷ comprised three phases – brainstorming, sorting, and rating, which took place between August and November 2016. Sixty-five people from all over the world took part in the brainstorming phase, thereby generating 99 statements in response to the prompt – “an essential feature of a higher education institution’s learning analytics policy should be....” Seventy-five LA experts were invited to participate in the sorting (sorting the 99 statements according to shared themes) and rating (by ‘importance’ and ‘ease of implementation’ using a 7-point

Likert scale) stages, of whom 30 completed the sorting activity, 29 completed rating by ‘importance’, and 25 completed rating by ‘ease of implementation’. Among all the participants, 15.2 per cent of them reported to have intermediate-level of LA expertise, whereas 69.7 per cent to have advanced- or expert-level of LA expertise. The distribution of job roles of participants are shown in Figure 1.

The 99 statements generated by the participants were aggregated to reveal shared patterns in the collected data by applying statistical techniques of multidimensional scaling and hierarchical clustering. Visualisations then helped to grasp the emerging data structures and to interpret the data. One important aspect of GCM is its bottom-up approach. Instead of presenting a given set of criteria to sort and rate, the community itself generates the ideas that are to be clustered and rated by a group of participants who have substantial research or practice experience with LA.

Figure 1. Job roles of GCM participants



⁷http://bit.ly/SHEILA_GCM

3.3 INSTITUTIONAL LEADERS – SURVEY AND INTERVIEWS

3.3.1 SURVEY

The survey⁸ consisted of 28 questions that explore the adoption status and maturity of LA among European HEIs. The adoption status section includes questions investigating existing LA initiatives, institutional infrastructure for LA, adopted strategy and policy for LA, considerations of legal and ethical issues, and existing evaluation frameworks. The LA maturity section asks participants to self-evaluate the engagement of key stakeholders (i.e., teaching staff, students, and managers), success of LA, institutional culture, data and research capabilities, legal and ethical awareness, and existing training. The survey was distributed widely among European HEIs, of which 46 from 22 countries responded (response rate: 15%). This activity lasted from September 2016 to February 2017. A descriptive statistical analysis was carried out on the data.

3.3.2 INTERVIEWS

Sixty-four interviews were carried out between August 2016 and February 2017, and 51 higher education institutions across 16 countries took part in this activity. Among these institutions, nine also participated in the institutional survey⁹. The participants in the interviews ranged from Vice Principals/Deans of Learning and Teaching to Heads of IT, Directors of E-learning Centres, and positions established specially for LA research and development. Each of these interviews lasted for 30 to 60 minutes. The number of participants in each interview ranged from one to three, and some participants from the same institution attended the interviews separately. This resulted in a total number of 78 participants from 51 institutions. Ten interview questions¹⁰ were developed to investigate (1) institutional plans for LA, (2) motivations for LA, (3) adopted strategy, (4) strategy development processes, (5) readiness preparations, (6) success and evaluation, (7) success enablers, (8) challenges, (9) ethical and privacy considerations, and (10) the interviewee's views of essential elements in a LA policy. Before the interviews started, the researchers explained the meaning of LA to all interviewees to ensure a shared understanding. All interviews were carried out online and video-recorded with consent received from the participants in advance.

The data was analysed in two phases. In the first phase, we used recursive abstraction to condense data in summary forms according to each research question. This allowed us to identify emerging themes across cases. The results informed the second phase – a thematic analysis. A coding scheme¹¹ consisting of two types of variables (implementation and readiness) was developed to assist us with interrogating the data in a systematic way. The implementation variables include fourteen groups of thematic codes that capture the different aspects of institutional LA implementation: goals, approach, primary users, scope, educational data warehouse, analytics elements, interventions, evaluation, strategy development, experience, ethics, policies, challenges, and success. The readiness variables include seven groups of thematic codes that represent different critical factors affecting the readiness of institution for LA adoption: technology, funding, leadership, stakeholder involvement, analytical capabilities, analytical culture, and policy conceptualisation. Each of these themes contain two to eleven codes, resulting in a total of ninety-nine codes.

⁸http://bit.ly/SHEILA_institutional_survey

⁹Altogether, the institutional survey and interviews reached out to 88 higher education institutions from 26 European countries.

¹⁰http://bit.ly/SHEILA_institutional_interviews_questions

¹¹http://bit.ly/SHEILA_institutional_interviews_coding

3.4 STUDENTS – SURVEY AND FOCUS GROUPS

3.4.1 SURVEY

The student survey¹² was designed to measure ideal expectations (what users desire) and predicted expectations (what users expect in reality) of LA [18]. Twelve questions were designed to investigate expectations for LA services (beliefs about the likelihood that future implementations and running of LA services will possess certain features). The variance of the items is explained by a two-factor structure of Ethical and Privacy Expectations and Service Expectations. The Ethical and Privacy Expectations factor refers to student beliefs regarding the ethical procedures involved in LA services (e.g., the university will obtain consent for the collection and analysis of any educational data), whereas the Service Expectations factor refers to how students would like to benefit from LA services (e.g., students receiving regular updates about their learning progress) [19].

The survey was carried out in six European HEIs between April and October 2017, with a total number of 3,053 responses. To develop and validate the survey, an iterative method was used wherein factor analysis (exploratory and confirmatory) was used to refine the number of items and assess the validity of the scales. Additional analyses were also conducted, which included the assessment of measurement invariance and latent class analysis.

3.4.2 FOCUS GROUPS

Eighteen student focus groups were carried out in four European HEIs between January and June 2017, involving 74 students in total. The focus group interviews were semi-structured, each lasting about an hour. As the adoption of LA was at a rather early stage in these institutions, ten different questions¹³ were designed to understand the awareness and attitudes of participants towards existing data practices, which the interviewer drew upon to guide participants to consider the potential benefits and challenges of using student data for LA. All participants received a short introduction to the concept of LA before the focus group interviews started. Before the focus groups started, all participants signed a consent form to participate in the study and have their conversations recorded.

The data was analysed in two phases, following the same methods employed to interrogate the interview data (see Section 3.3.2). A coding scheme¹⁴ consisting of 64 codes categorised into 3 main themes and 14 sub themes was developed to enable the thematic analysis in the second phase.

¹²http://bit.ly/SHEILA_student_survey

¹³http://bit.ly/SHEILA_student_FG_questions

¹⁴http://bit.ly/SHEILA_student_FG_coding

3.5 TEACHING STAFF – SURVEY AND FOCUS GROUPS

3.5.1 SURVEY

The staff survey¹⁵ consisted of 16 questions based on the same framework adopted to develop the student survey. It was distributed among four European HEIs and received a total number of 210 responses. Given the sample number of responses to the teaching staff survey for each locale, the use of factor analytic methods was unsuitable. Therefore, only descriptive statistics for the 16 items are presented.

3.5.2 FOCUS GROUPS

Sixteen staff focus groups were carried out in four institutions between May and October 2017, involving 59 teaching staff in total. The procedure followed the one adopted to carry out student focus groups, and the questions¹⁶ were adapted using student focus group questions. The data was analysed using a coding scheme¹⁷ consisted of 59 codes categorised into 4 main themes and 26 sub themes.

3.6 RAPID OUTCOME MAPPING APPROACH

The SHEILA framework was developed based on data collected from the aforementioned research activities, using the Rapid Outcome Mapping Approach (ROMA). The ROMA model was designed by the ODI (Overseas Development Institute) to inform policy processes in the field of international development using research evidence [21], and has been adapted to guide the planning and implementation of LA at an institutional level [5, 8]. The adapted model (Figure 2) begins by defining an overarching policy objective, followed by six steps designed to provide policy makers with context-based information: (1) map political context, (2) identify key stakeholders, (3) identify desired behaviour changes, (4) develop engagement strategy, (5) analyse internal capacity to effect change, and (6) establish monitoring and learning frameworks. Unlike traditional linear tools and approaches, ROMA is designed to be used iteratively (as the spiral arrows indicate) to inform strategic choices and

meet unexpected changes (or challenges) in a complex setting.

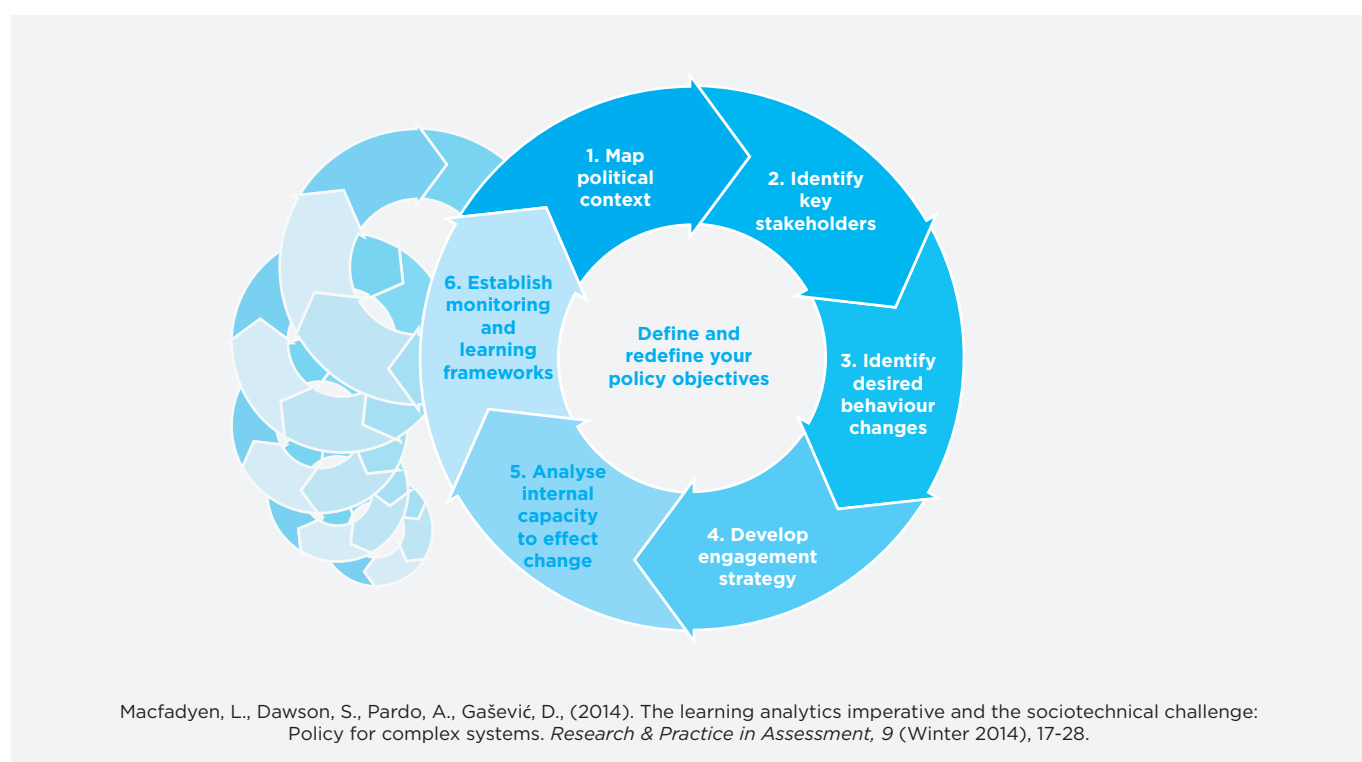
We used the ROMA model as an additional coding scheme to analyse each of the 51 institutional cases (64 interviews) by mapping out their LA-related activities and challenges to each of the six dimensions in addition to the desired objectives, so as to identify the strategic approaches (key actions) that HEIs have taken to adopt LA. Based on the mapping results of key actions and challenges, and the interviewees' views of essential elements to include in a LA policy (interview question 10), we developed a list of questions, treated as 'policy prompts', to address when developing a LA policy. Following this, we used the same method to analyse data collected from GCM, student focus groups, and staff focus groups to reflect the perspectives of a wide range of stakeholders. The two phases of analysis led to the first two versions of the SHEILA framework.

¹⁵http://bit.ly/SHEILA_staff_survey

¹⁶http://bit.ly/SHEILA_staff_FG_questions

¹⁷http://bit.ly/SHEILA_staff_FG_coding

Figure 2. The RAPID Outcome Mapping Approach [8]



3.7 ETHICS

All the research activities follow the ethical guidelines developed by British Education Research Association (BERA).

The initial ethics approval was received from Moray House School of Education Ethics Committee at the University of Edinburgh.

3.8 LIMITATIONS AND FURTHER STUDY

The SHEILA project focused on cases of adoption of LA in Europe. Although the sample was considerably large, we acknowledge that the observations could limit to a particular social and cultural context in Europe. For example, under the governance of European General Data Protection Regulation [14], certain awareness and challenges around ethical and privacy issues may be common in the European context, but not beyond. In addition, the surveys and focus groups with teaching staff and students were limited to four European HEIs, with the exception of the student survey, which covered two additional HEIs. This means evidence drawn from these sets of data particularly reflects the specific contexts of these institutions.

While it is not possible and not intended to generalise the findings, the project serves the purpose of informing future work on LA policy and strategy within and beyond higher education.

4. Results and discussion

In this section, we present the results of a group concept mapping activity, a survey and interviews with institutional leaders, a survey and focus groups with teaching staff, and a survey and focus groups with students.

The four sub-sections are organised according to the research questions below:

1. What is the state of the art in terms of LA adoption among European HEIs?
2. What are the key drivers for LA from the perspectives of institutional leaders, teaching staff, and students?
3. What are the key challenges for LA from the perspectives of institutional leaders, teaching staff, and students?
4. How can we move towards systematic adoption of LA in higher education?

Figure 3. The adoption of LA (interviews)

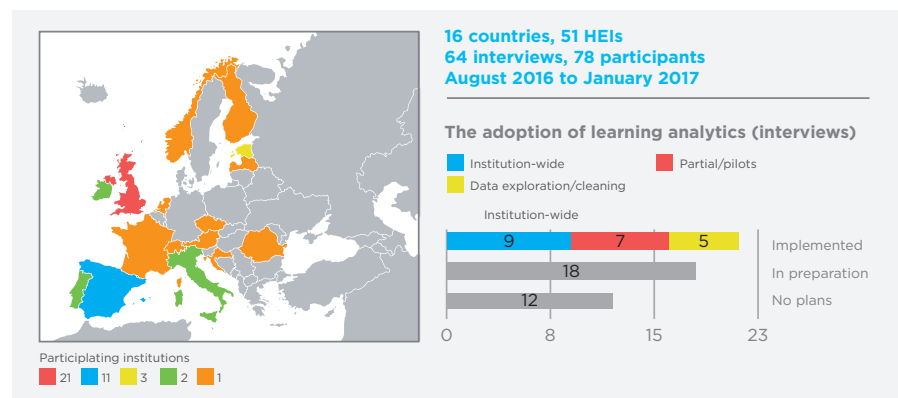
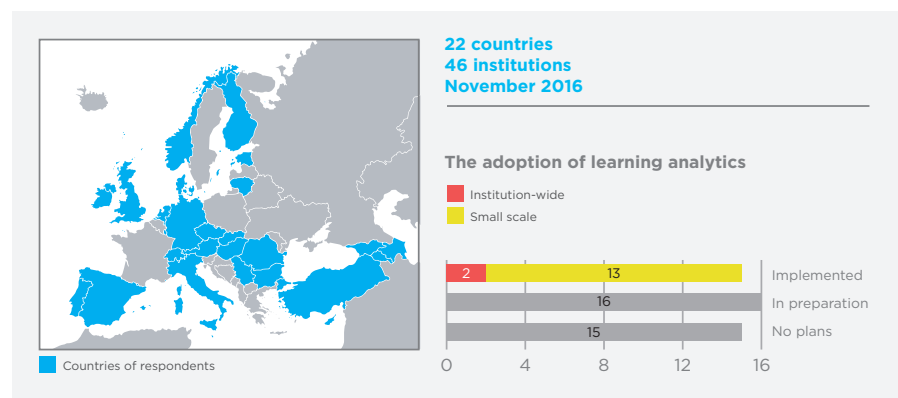


Figure 4. The adoption of LA (survey)



4.1 LEARNING ANALYTICS IN EUROPEAN HIGHER EDUCATION - THE STATE OF THE ART

4.1.1 ADOPTION STATUS

At the time of the interviews, 21 out of 51 institutions already implemented centrally-supported LA projects, 9 of which had reached institution-wide level, 7 partial-level (including pilot projects), and 5 were at a data exploration and cleaning stage. Meanwhile, 18 institutions were in preparation to roll out institutional LA projects, and 12 did not have any concrete plans for an institutional LA project yet (Figure 3).

An equivalent question in the survey (n=46) revealed that 15 institutions had implemented LA, of which 2 had reached full implementation and 13 were in small scale testing phases. Sixteen institutions were in preparation for LA projects, and 15 were interested but had no concrete plans yet (Figure 4).

The results showed that over two thirds of institutions that participated in the interviews or survey had implemented LA or were preparing to do so. However, when asked whether they have achieved the goals set out for LA, few participants were able to claim success. For example, among the institutions that responded to the survey, only 3 out of the 15 institutions that have implemented LA 'agreed' that they have achieved the goals. Nevertheless, several participants of the interviews indicated an observation of short-term wins, such as experience-gain, cultural change, infrastructural upgrade, and a better understanding of legal and ethical implications. In particular, institutions that have implemented small-scale pilot projects found the experience beneficial in terms of achieving the above-mentioned objectives and reshaping a strategy for wider adoption.

4.1.2 APPROACHES AND STRATEGIES

It was noted that most institutions that participated in the interviews took a problem-led approach to LA; that is, they adopted LA to tackle pre-identified problems (e.g., retention, progression, and student satisfaction). Two other popular approaches

are (1) exploratory approach: institutions adopted LA as a means to understand a phenomenon (e.g., how students learn, how students engage with learning resources, and how teachers engage with the online platform); and (2) measuring approach: institutions used LA as a tool to measure a phenomenon (e.g., student performance, student retention, and teaching

performance). Governmental requirements for quality assurance often led to this approach. Similarly, a survey question that investigated how institutions adopted LA to solve pre-identified problems highlighted measuring and exploratory approaches as a prevailing phenomenon (see the top three approaches in Table 3):

Table 3. Approaches to LA – survey

Q: Which of the following statements best describe how your institution is attempting to solve the identified problems?	Counts	% by respondents (n=46)
We measure learning performance.	38	83
We try to understand how students learn.	27	59
We try to identify learning bottlenecks.	27	59
We produce reports based on institutional data.	22	48
We measure teaching performance.	20	43
We send alerts to students based on analytics results.	20	43
We send alerts to teaching staff/ tutors based on analytics results.	16	35
We predict learning outcomes based on institutional data.	10	22
Other.	3	7

Many institutions involved in the interviews have not defined clear strategies for LA, whereas those that have implemented centrally-supported projects or planned to do so often initiated LA under wider digitisation strategies or teaching and learning strategies. Nevertheless, a number of institutions have started the process by setting up a steering committee. Similarly, in response to the survey question – “does your institution implement LA under any strategic framework,” among the 15 institutions that have implemented LA, only 3 of them claimed to have a clear strategy. This was reflected in an observation of a lack of

evaluation processes among the institutions in both interviews and survey. A large number of institutions involved in interviews indicated that they had not reached the stage of considering evaluation yet, while a small number of cases suggested that LA would be evaluated using their institutional key performance indicators. Similarly, the survey showed that among the 15 institutions that have implemented LA, only 4 have developed success criteria. In general, the interviews presented a picture mixed of a bottom-up approach driven by the interest of individual researchers and a top-down approach driven by the managerial board,

without the two approaches necessarily converging in one institution.

4.1.3 SUMMARY

In summary, the state of adoption of LA was in early phases among European HEIs (with most of them ranging from showing interest to exploring the availability of data and piloting projects). Few institutions had defined strategies or monitoring frameworks to guide the adoption of LA, and the claimed success tended to focus on addressing cultural and social challenges related to LA.

4.2 KEY DRIVERS FOR LEARNING ANALYTICS

4.2.1 SENIOR MANAGERS

From the perspectives of senior managers, three clear internal drivers for LA were identified:

1. Learner-driver: to encourage students to take responsibility for their own studies by providing data-based information or guidance.
2. Teaching-driver: to identify learning problems, improve teaching delivery, and allow timely, evidence-based support.
3. Institution-driver: to inform strategic plans, manage resources, and improve institutional performances, such as retention rate and student satisfaction.

In addition, various external drivers have been identified, including the results of external evaluations or audits and obligations to provide quality reports. A survey question that investigated institutional motivations to adopt LA revealed that the top four drivers were to improve learning performance, student satisfaction, teaching excellence, and student retention (Table 4). These drivers also reflect common indicators of institutional performance. Interestingly, 'to explore what LA can do' came up as the fifth popular driver. This shows that more than half of the respondents were still at a very early stage of adoption. Despite the high interest, there was a sense of uncertainty towards LA.

Aligned with the survey results, institutional interviews showed that institutional motivations for LA were driven by performance indicators, and the sense of uncertainty was mainly caused by concerns about the return on investment, given that contextual relevance and benefits of LA were still unclear to some institutions. A few interviewees confided that they were under the pressure to adopt LA due to the technology push, despite the fact that 'the need' for LA was still to be defined in these institutions.

Table 4. Institutional motivations for LA – survey

Q: What are the motivations for your institution to adopt learning analytics?	Counts	% (n=46)
To improve student learning performance.	46	0.87
To improve student satisfaction.	33	0.72
To improve teaching excellence.	33	0.72
To improve student retention.	26	0.57
To explore what learning analytics can do for our institution/staff/students.	25	0.54
To provide personalised learning support.	18	0.39
To increase learning motivations.	17	0.37
To inform curriculum.	16	0.35
To encourage self-regulated learning.	14	0.30
To improve student-teacher communication.	12	0.26
To improve student recruitment.	11	0.24
Other.	1	0.02

4.2.2 TEACHING STAFF

From conversations with teaching staff, we observed a strong interest in using LA to get an overview of students' learning progress and their engagement with learning materials. The motivation here is to improve learning experiences and adapt the curriculum to meet the needs of learners. For example, the Spanish and UK focus groups desired to know the 'usefulness' of resources and the preferences of students

towards learning materials. The Estonian focus groups expressed an interest in enabling personalised support to second language speakers, and the Dutch focus groups showed an interest in evaluating the workload of students who were mostly part-time learners.

While the survey (Figure 5) results aligned well with the abovementioned findings (having access to the learning progress of students), they also highlighted a particular

gap between staff's ideal expectation (what users desire) of receiving feedback in an understandable format and their predicted expectation (what users expect in reality) of this to happen. This indicates a need for further development in the research and design of LA-enabled feedback to better meet the needs of teaching staff in this particular aspect.

4.2.3 STUDENTS

The results of the focus groups showed that there was a strong interest in using LA to enhance student experiences, particularly in areas such as the provision of timely feedback, easy access to digital resources, and personalised learning support. In addition, students valued face-to-face conversations with tutors and lecturers, which was believed to be a solution to several identified issues such as missing

information about off-line learning activities and misinterpretations of data.

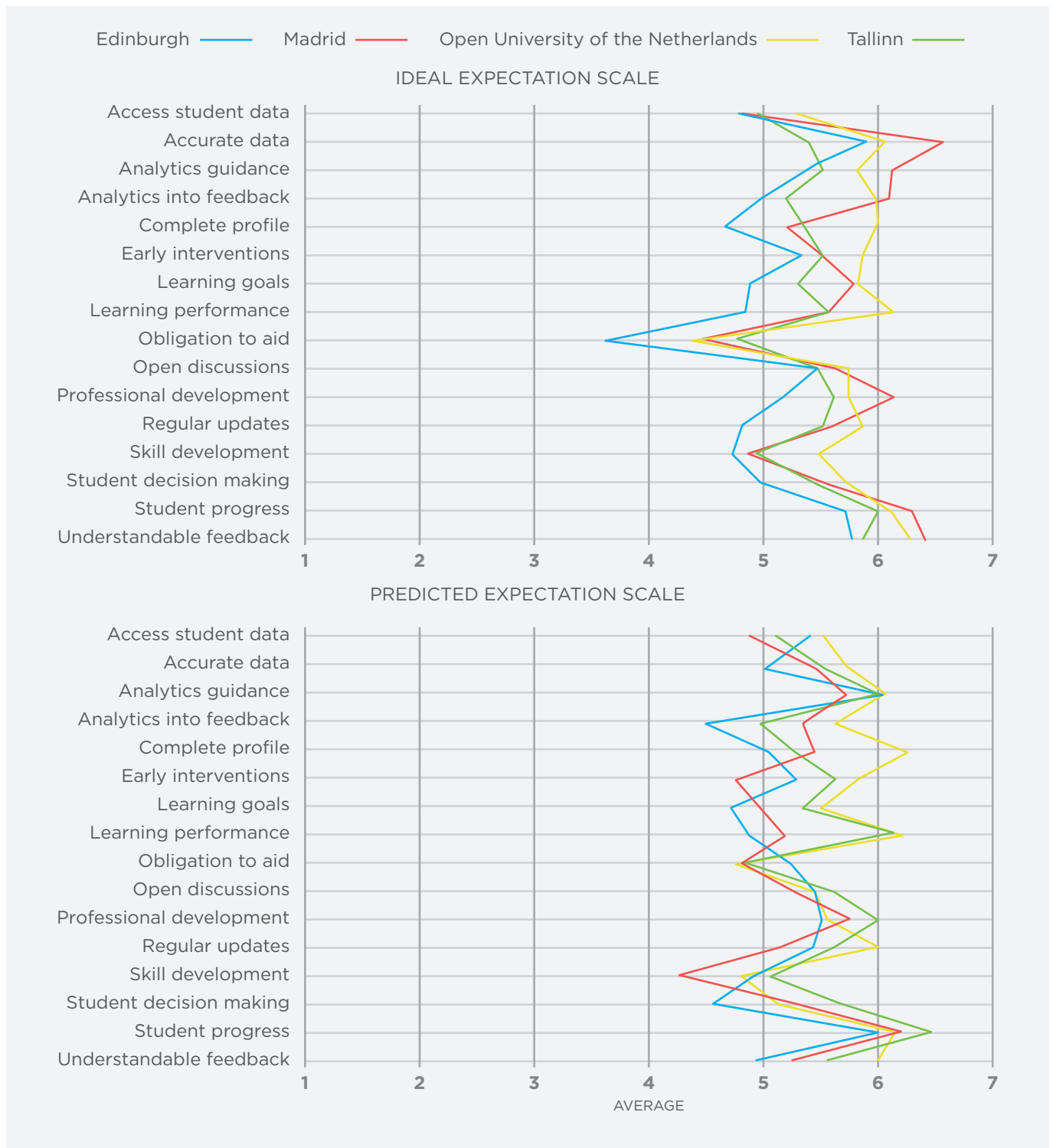
The survey responses showed student expectations of LA services to be higher for those features associated with self-regulated learning, specifically towards receiving a complete profile of their learning, making their own decisions based on the analytics results, and knowing how their progress compares to a set learning goal (Figure 6). Even though the average responses tended

to be similar across locations, the sample of students from the Open University of the Netherlands were found to have lower ideal expectations towards receiving complete profiles across modules based on LA, compared to the other samples. This highlights that there is no one-size-fits-all LA solution, and further investigation into the preference of students towards the access to their learning data at this particular institution is needed.

4.2.4 SUMMARY

In summary, senior managers were most interested in using LA to improve institutional performance, whereas teaching staff to reform curriculum and improve student support, and students to receive more personalised education tailored to meet their needs.

Figure 5. Staff expectations of LA¹⁸



¹⁸http://bit.ly/SHEILA_staff_survey

Figure 6. Student expectations of LA (service variables)¹⁹



¹⁹http://bit.ly/SHEILA_student_survey

4.3 KEY CHALLENGES FOR LEARNING ANALYTICS

The systematic literature review [15] that focused on 23 empirical studies of institution-level adoption of LA across the world observed several challenges related to strategic planning and policy. These can be summarised in six areas:

1. There is a shortage of leadership capabilities to ensure that implementation of LA is strategically planned and monitored.
2. There are infrequent institutional examples of equal engagement with different stakeholders at various levels.
3. There is a shortage of pedagogy-based approaches to removing learning barriers that have been identified by analytics.

4. There are insufficient training opportunities to equip end users with the ability to employ LA.
5. There are a limited number of studies empirically validating the impact of analytics-triggered interventions.
6. There is limited availability of policies that are tailored for LA-specific practice to address issues of privacy and ethics as well as challenges identified above.

These challenges underline the need to develop a comprehensive policy that meets the requirements of LA and considers multiple dimensions including an institution's context, stakeholders therein, pedagogical applications, institutional capacities, success evaluation, legal and

ethical considerations, and a strategy that aligns with the institution's missions.

While aligning with the findings of the literature review, our direct engagement with key stakeholders in various research activities further highlighted three areas of challenges that needed to be addressed to ensure the impact of LA:

1. Ethics and privacy
2. Institutional capacity
3. Closing the feedback loop effectively

We present our observations in the following sections accordingly.

4.3.1 ETHICS AND PRIVACY

The group concept mapping activity collected 99 statements from 65 LA experts based on the prompt – “an essential feature of a higher education institution's learning analytics policy should be....”. These statements were clustered into six key themes (Figure 7):

1. Privacy and transparency
2. Roles and responsibilities
3. Objectives of learning analytics
4. Risks and challenges
5. Data management
6. Research and data analysis

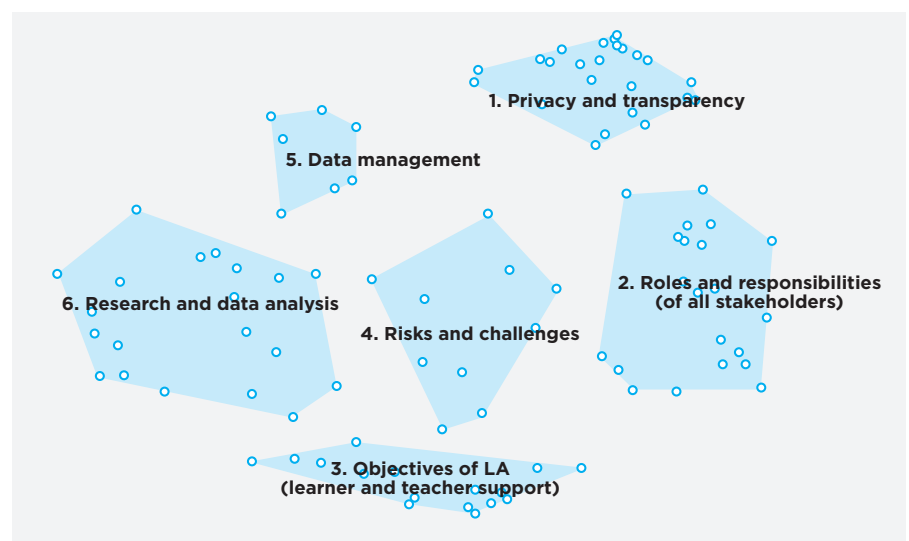


Figure 7. Group concept mapping – cluster map

“

“If a student chooses not to engage with learning analytics, well, legally they can still be a student here, it doesn’t stop them being a student, but is the University doing the best by that student if they choose not to? I think it’s a very very very fine line.”

– institutional leader

The results of the rating phase showed that “privacy and transparency” related statements were considered as the most important aspect of a LA policy, and interestingly also the easiest to implement in a policy document (Figure 8). By contrast, “objectives of learning analytics” is less easy to address than other themes, perhaps due to the perceivable gaps of understanding and expectations among different stakeholders, as previously identified in the literature review [16].

From the perspectives of senior managers, as observed through interviews, ethical and privacy issues were not only perceived as a barrier to gain support from teaching staff and students, but also a stopper to ‘experiment’ on LA, especially under the constraints of existing data protection laws. For example, several institutions have pointed out in the interviews the lack of effective technological solutions to ensure opt-in/-out options without affecting the quality of data or disadvantaging students. An ethical dilemma has also emerged alongside this challenge; that is, losing an opportunity for institutions to fulfil its onus to provide students with the best educational services. Also related to managerial decisions was the dilemma in using LA to promote inclusive education by giving personalised support while seemingly restricting certain support to particular groups of students only.

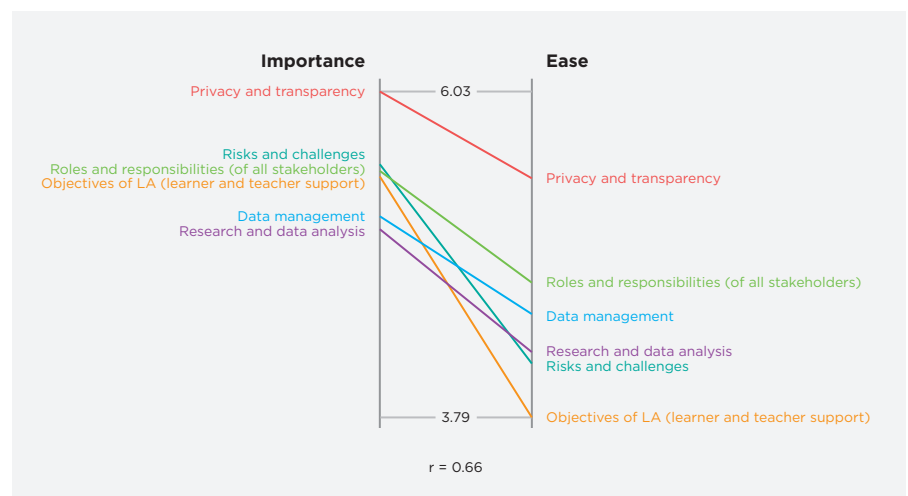


Figure 8. Group concept mapping - rating ladder graph

The focus group interviews with teaching staff identified three types of concerns: teacher-centred, student-centred, and LA-centred. The student-centred concerns particularly highlight issues around ethics and privacy. The following themes emerged during the analysis process:

1. Profiling students and unequal support
2. Autonomy deprivation and privacy intrusion
3. Risks of demotivation and inducing anxiety
4. Behaviour alteration due to surveillance

Unsurprisingly, the concerns raised by the participants of student focus groups were centred around ethical and privacy implications in the use of their data.

The following aspects particularly received the most attention:

1. Data access
2. Data security
3. Data anonymity

Figure 9. Student expectations of LA (ethics and privacy variables)²⁰



The students were averse to any form of data collection that might put students under surveillance or produce stereotypes as a result of data being made available to teaching staff. They also tended to object to the idea of the university sharing student data with external partners, for the fear of becoming commercial targets.

“

“People would think that they’re being looked under a microscope, which would kinda invade their privacy.”

– student

“

“I think if the tutor comes in there with the perception, ‘oh she’s the one that’s been really struggling the whole time’, even though you do very well in that particular course, I think it would affect the tutor’s perception of you.”

– student

Similarly, the results of the student survey showed high expectations towards the university dealing with ethical and privacy issues around the use of their data (Figure 9). In particular, this statement received the highest average response: ‘The university will ensure that all my educational data will be kept securely.’ In comparison, the expectation to provide consent before educational data is collected and analysed received the lowest average response within these items. While students agreed with the latter belief, it verged on indifference on the predicted expectation scale for the Spanish student sample (Madrid). One possible interpretation is that the respondents were open to the university to collect and analyse educational data for routine reporting (e.g., attendance and immigration purposes) and educational offerings (e.g., teaching and learning support).

Another interesting topic that particularly emerged from the discussions with staff and students is around ‘agency’. On the one hand, LA is based on the idea of empowering students in making learning-related decisions. On the other hand, it ‘datafies’ students in the process of collecting, analysing and interpreting data. Teaching staff, in particular, raised the concern about

spoon-feeding students and removing the opportunity to learn from failures, whereas students were worried about being treated as ‘numbers’.

“

“The more we start identifying individual students, ‘well, you need a remedial class because you’re underperforming’, you’re kind of taking that agency away from students. And I think there is a very big danger of this kind of approach...Spoon feeding students, telling them what they have to know, giving them sort of tests and stuff, has been the way that universities responded to poor satisfaction scores, poor teaching scores, or whatever it is.”

– teacher

²⁰http://bit.ly/SHEILA_student_survey

A common finding across survey and focus groups with both teaching staff and students is the low expectation of teaching staff's obligation to act when students are found to be at-risk of failing or underperforming (see Figure 6). The participants in student focus groups expressed low interest in using LA to alert teaching staff about individual students'

performance. One student from the Dutch focus groups pointed out that it is not the teachers' responsibility to 'save' every student in higher education, as opposed to the need to do so for school children who are still developing decision-making skills.

The desire to maintain student agency observed among teaching staff and students pointed to a need to examining existing data-processing procedures in HEIs. The results of the institutional survey showed that there is still much work to be done in this area (Table 5 & Table 6):

Table 5. Autonomy granted for students among institutions that have implemented LA projects (n=15) – survey

Q: What levels of autonomy are students granted at your institution in terms of learning analytics implementation? (Tick all that apply.)	Status: implemented
There is a formal process for students to correct their personal data.	4
There is a formal process for students to raise complaints regarding the use of their data.	1
There is a formal process for students to question the accuracy of learning analytics results.	1
Students identified as at risk have the right to refuse support provided by teaching staff/tutors.	1
None of the above at the moment.	10
Other.	0

Table 6. Autonomy granted for students among institutions that were preparing to (n=16) or were interested in implementing LA projects (n=15) – survey

Q: What levels of autonomy will/would students be granted at your institution in terms of learning analytics? (Tick all that apply.)	Status: preparation	Status: interested
There will/would be a formal process for students to correct their personal data.	6	8
There will/would be a formal process for students to raise complaints regarding the use of their data.	4	7
There will/would be a formal process for students to question the accuracy of learning analytics results.	3	7
Students identified as at risk will/would have the right to refuse support provided by teaching staff/tutors.	8	8
None of the above.	2	2
Other.	4	1

The respondents were divided into three groups by their experience of LA (already implemented: n=15; preparing to implement: n=16; interested in implementing: n=15). The results showed that two thirds of the 'implemented' group did not have a

defined procedure to grant autonomy for students in terms of LA services, whereas the 'preparation' group expressed a higher expectation for this to happen, and the 'interested' group even more so. The patterns observed among the three groups of answers

implicate a rising awareness of this area as well as possible challenges in facilitating the above-mentioned procedures in reality despite the high expectation of these to happen.

4.3.2 INSTITUTIONAL CAPACITY

Institutional capacity for LA encompasses multiple dimensions. One institutional survey question investigated into barriers to the success of LA adoption using a

categorical response with the following options: (1) not a barrier; (2) a small barrier; (3) a moderately-sized barrier; (4) a large barrier; and (5) a critical barrier. The results showed that each of the pre-identified barriers was considered as an at least

moderately-size barrier by more than half of the respondents (Table 5). Among these, analytics expertise, data culture, staff buy-in, and technological infrastructure came as the top barriers respectively (n=46):

Table 7. Barriers to the success of LA adoption – survey

To what degree would you consider the following elements to be barriers to the success of learning analytics at your institution?	Moderately-size to critical barrier	% (n=45)
Analytics expertise	34	0.76
A data-driven culture at the institution	30	0.67
Teaching staff/tutor buy-in	29	0.64
The affordances of current learning analytics technology	29	0.64
Current infrastructure for data storage and management	27	0.60
Legal framework	27	0.60
Privacy protection	26	0.59
The capabilities of staff and students to understand learning analytics results	26	0.58
Investment in research related to learning analytics	26	0.58
Ethics guidelines	26	0.58
Institutional strategy	25	0.57
Student buy-in	25	0.56
Senior manager buy-in	24	0.53

These barriers were also repeatedly mentioned in interviews and focus groups. Several institutional leaders pointed out the analytics skills gap between IT professionals and academics, whereas teaching staff pointed out the difficulty to understand ‘black box’ algorithms.

The lack of knowledge or skills required to comprehend the results generated by LA has led to distrust and resistance to LA. In some cases, this challenge stopped teaching staff from seeing LA as a useful resource for teaching.

The lack of a data-driven culture and support for LA was partly due to the low awareness of the benefits of LA, and partly due to the perception of LA as a burden on existing workload, especially among teaching staff. This was shown in a prevailing problem of lacking a common understanding between decision makers and decision implementers in terms of the efforts required to realise a vision.

“

“The cleverer the algorithm, the more opaque and therefore the more dangerous it is... We don’t know what biases are actually built into the data...”

– teacher

“

“We are offering a high-quality industrial scale education, and I think it would be a real mistake to start confusing that message by doing things that suggested that we could.... We say there’s an individual member of staff who is looking out for you, but that member of staff doesn’t have time to actually do it.”

– teacher

“

“In large groups, it is very difficult to provide personalized support. I think the limit is 20 people. [...] If there are 200 students, I think it will be impossible even with LA”

– teacher

The main issue here is that teaching staff found it difficult to embrace a new technology that seemed to demand on a significant amount of time to learn to operate and to wade through information.

In addition to challenges around data capabilities and culture, obtaining an enabling infrastructure for LA has been a challenge particularly identified by institutional leaders. This challenge often emerged in the early phase when institutions explored LA.

While a great number of institutions have sought solutions offered by external partners, some of the interview participants (senior managers) pointed out the struggle to find a suitable data solution due to the fact that existing LA systems offered by vendors tended to focus on solving retention problems, and hence were not applicable to institutions that did not intend to use LA primarily for this purpose. Similarly, the problem of no one-size-fits-all solution existed within an institution where some subjects were identified with lower completion rates than others.

4.3.3 CLOSING THE FEEDBACK LOOP EFFECTIVELY

A LA cycle involves four key elements: (1) learners, (2) data, (3) metrics, and (4) interventions [3]. These elements are interwoven in a feedback loop. The activities that learners carry out in learning environments allow certain types of data to be generated and captured, followed by data being processed into metrics or analytics that provide insights into a learning process or possible outcomes. Based on the information derived from analytics, interventions are designed to support learners, such as providing dashboards to monitor learning progress or alerting students with personal

messages. A number of challenges that might impede loop closure have been raised by teaching staff. These concerns centre on linking data to learning, to impacts, and to action.

Firstly, there were prominent concerns about the usefulness of data and the difficulty to measure or define learning in a way that applies to every individual.

“

“What you can’t really tell and even our assessment is not great at this... is their learning. That’s something that happens in the brain, in their mind. And I would be very cautious about casually equating behaviour and performance with learning.”

– teacher

“

“I don’t want it [LA] to make all of the students behave in the exact same way to satisfy an algorithm. I want it to enable students to have the best experience in whatever that experience is. You know, you can be totally different from everyone else and still do perfectly fine.”

– teacher

These quotes reflect a common challenge in making a meaningful interpretation of data generated by LA in such a way that reflects every student’s learning situation and respects their differences in learning approaches. In addition, the fact that LA can only capture and present a partial picture of learning (particularly with the limitation to digital data only) has led to questions about its efficacy in informing decisions, its applicability to different subject areas, and its risk of prioritising algorithms over teaching professionalism. In light of this, teaching staff highlighted the importance to include pedagogy expertise in the design of LA, and to provide sufficient training that enhances teaching staff’s data literacy and skills to carry out learning supports based on information obtained from LA.

Secondly, there were concerns about the potential impacts on the psychological states of students as a result of LA. For example, the awareness of ‘being watched’ could lead to conscious or unconscious alterations in behaviour that do not necessarily benefit learning.

“

“We put in a system where we give them swipe cards and they swiped in to the lecture. And one of my colleagues who put it in came into the coffee room bright red in the face, because about two weeks in he heard beep, beep, beep, beep, beep, beep and nobody came in...As soon as they realised they were being monitored...the students started subverting it.”

– teacher

This points to the interpretation issue mentioned earlier that behavioural data does not necessarily indicate whether learning is occurring or not. In addition, there is a potential of demotivating students or leaving them unnecessarily anxious as a result of analytics data being made available to them if without proper follow-up support.

“

“How the student might interpret that message or information might be problematic. I’d want to know how I need to deal with that.... For example, if we are to tell students they’re failing at week five, how do we tell them in a way that isn’t going to make them more anxious?”

– teacher

Thirdly, analytics data does not always invoke objective and critical reflections among recipients to produce constructive behaviour. Both teachers and students need to have sufficient data literacy to understand the information that is presented to them and to connect it to actions. The latter is twofold in that they not only need to trace the data back to the actions that generate it, but also have the ability to plan and carry out actions forward to improve learning. More importantly, students need to care about acting on data.

“

“If you are doing worse than other people it certainly could make you feel bad. And if you’re doing better than other people, it might actually demotivate you because you’re like, ‘Oh I’m doing fine and forget it.”

– teacher

“

“We can identify them but what can we do about it? You know, we tried a few sort of interventions. The problem is that people are already disengaged. They’re unlikely to engage with anything that we try to do at that point. Intervene and say, ‘how can we offer you support?’ It’s like speaking into a black hole sometimes.”

– teacher

This points to the problems of unmatched perceptions of what can be achieved, disconnected understanding of what is required to achieve certain goals, and uncoordinated interests in LA among different stakeholders.

4.3.4 SUMMARY

In summary, the observed challenges of scaling up the adoption of LA are intertwined with the actors in an institutional network. For senior managers, the challenges are at the operational level, such as obtaining sufficient funding, infrastructural, and human resources to enable LA, in addition to gaining support from the ground-level teaching staff to realise a vision. For teaching staff, the challenges are at pedagogical level in terms of defining, measuring, and supporting learning. For students, the challenges are at psychological and social levels, such as implications for privacy and impacts on autonomy and equity.

4.4 MOVING TOWARDS SYSTEMATIC ADOPTION

From our conversations with different stakeholders, a dialogic approach has been emphasised as a way to deal with the social and cultural challenges associated with LA. In this section, we present the views from different stakeholder on this particular point, and illustrate the SHEILA framework²¹ that has been built based on different stakeholder's views on what LA should or should not do for them. In addition, we present four case studies to demonstrate how the SHEILA framework was adopted in the higher education context.

4.4.1 A DIALOGIC APPROACH

In light of the social and cultural challenges associated with LA, as discussed previously, both students and teaching staff emphasised that 'data cannot replace social interactions' and pedagogical expertise needs to be involved in making sense of data and supporting learners to take a meaningful action based on the data:

“

“See that this person is beyond just data.... not reducing a person just to the figures that are being shown on your laptop regarding the person's performance.... You have to understand why the numbers are coming.... I feel like interaction is the key...to understand the data you need to understand where it's coming from.”

– student

“

“The one thing that will improve the relationship between us as the University and them [students] is if they think there are members of staff here in this University who know who they are, and who care about them.... I would rather have a conversation between a member of staff and a student about that behaviour than some... potentially quite opaque algorithm feeding that judgement.”

– teacher

Here, we observed a resistance to the algorithmic control that has been pervasively used to enhance economic efficiency in educational contexts [20], and a call to reflect on how technologies mould people's emotional and cognitive interactions with each other and with the machine [2]. This highlights the importance of taking a dialogic approach to LA to ensure its impact and scalability. In the same vein, the approach helps cultivating a shared vision across the institution:

“

“A lot of the initial discussions you would have round about how people perceive the use of analytics. I think that's been a positive discussion and it's been a discussion that's allowed us to really open out the people involved in that discussion to a much more positive way of constructing and understanding learning analytics.”

– institutional leader

²¹<http://sheilaproject.eu/sheila-framework/>

“

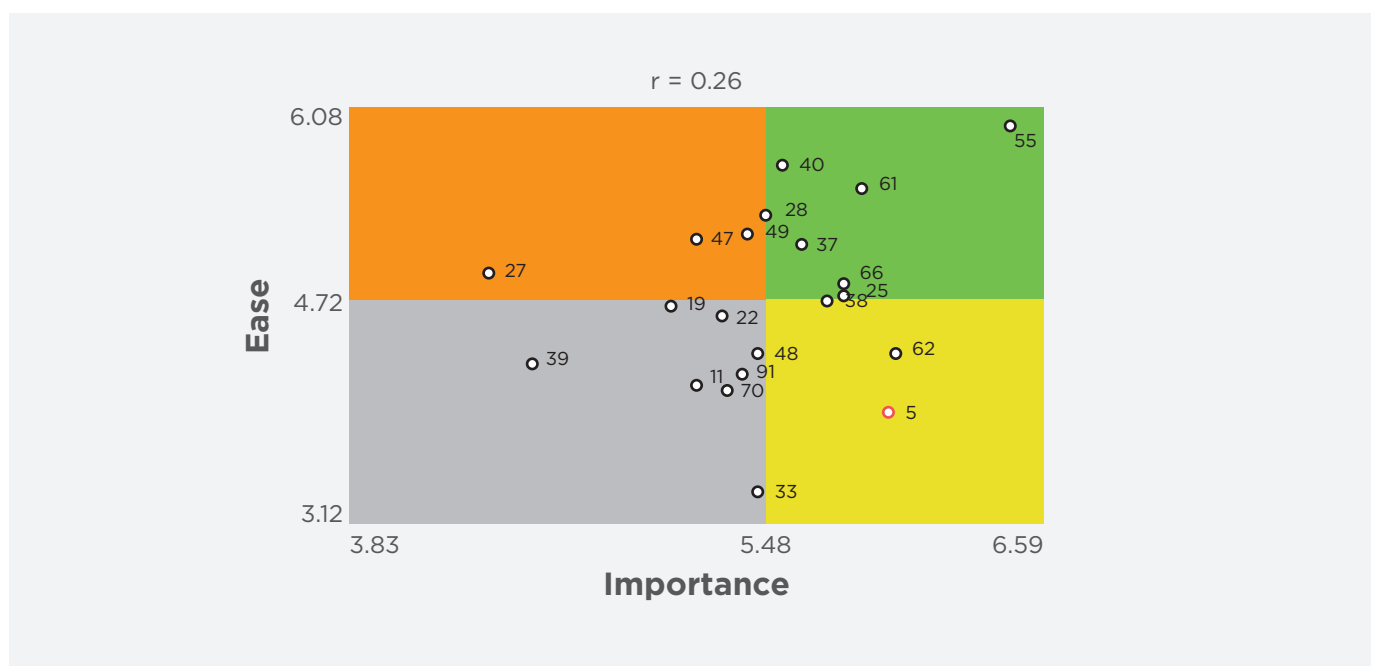
It also has the potential to address the following issue that was considered by LA experts as very important but relatively difficult to implement in a LA policy when it comes to defining roles and responsibilities of stakeholders (Figure 10):

“To ensure clarity and consistency around the institutional objectives and personal benefits for staff and students.”

– LA expert (GCM, Statement 5)

With the “human element” at the heart, we move on to discuss a policy framework that has been designed to ensure that institutional adoption of LA meets the need of all stakeholders.

Figure 10. Go Zone - Roles and Responsibilities



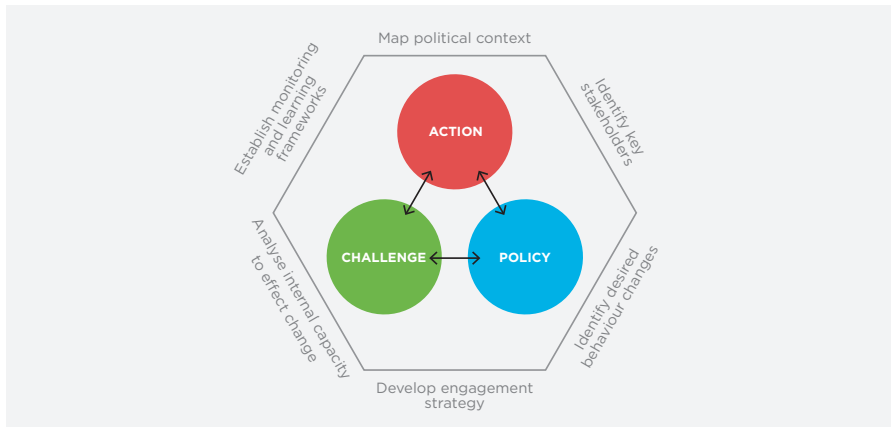


Figure 11.
The SHEILA framework structure

4.4.2 THE SHEILA FRAMEWORK

Our study identified a need for a policy to systematise the adoption of LA in HEIs. Based on the Rapid Outcome Mapping Approach (ROMA)[5, 8], a policy development needs to consider the following dimensions:

1. The political context of an institution – clarify drivers and purpose
2. The involvement of stakeholders – identify needs and concerns
3. A vision of change – visualise impacts
4. Strategic plans – design purposeful steps
5. Institutional capacity – assess the affordances
6. A monitoring framework – evaluate the efficacy and continue learning

Guided by these dimensions, we analysed all the data that we have collected to create a framework consisting of a collective experience from a wide range of European HEIs and the perspectives of multi-stakeholders. We started with an analysis of the interview data, which resulted in a list of 42 action points, 59 challenges, and 47 policy prompts across the six ROMA dimensions. This is the first version of the SHEILA framework²². Figure 10 explains the concept and structure of the SHEILA framework, in which action, challenge, and policy elements interact with each other [17].

During the analysis, we found a strong connection between the six ROMA dimensions; that is, the same challenge may be identified in multiple dimensions, and an

action may be informed by consideration of multiple dimensions at the same time. While the ROMA model is meant to be applied iteratively [8], there does not seem to be a definite order between the dimensions. Therefore, we decided to treat them as ‘dimensions’ rather than ‘steps’ as initially suggested by Young and Mendizabal [21], so as to acknowledge the fluidity between the six dimensions.

We further carried out an open coding analysis on the lists of actions, challenges, and suggested policy questions, and identified common themes including capabilities, culture, ethics & privacy, evaluation, financial & human resources, infrastructure, internal & external support, management, methodology, purpose, and stakeholder engagement. These themes helped us to identify the main focus of action in each ROMA dimension and prevalent issues to address. Dimension 1 (mapping political context) focuses on identifying the ‘purpose’ for adopting LA in a specific context so as to drive actions in the other dimensions. Dimension 2 (identify key stakeholders) is driven by the recognition that the implementation of LA in a social environment involves collective efforts from different stakeholders. Dimension 3 (identify desired behaviour changes) sets objectives, which reflect back to the ‘purpose’ of adopting LA. Dimension 4 (develop engagement strategy) defines approaches to achieving the objectives by addressing aspects that could otherwise become challenges, as identified in the literature: resources, ethics & privacy, and stakeholder engagement and buy-in (see Section 2.1). Dimension 5 (analyse internal capacity

to effect change) focuses on assessing the availability of existing resources (e.g., data and funding) and identifying challenges and risks. Dimension 6 (establish monitoring and learning frameworks) was the weakest in terms of existing plans for evaluation among the majority of the cases during the time of the study.

The SHEILA framework was subsequently updated with additional action points, challenges, and policy prompts based on data collected from GCM, student focus groups, and staff focus groups to reflect the perspectives of a wide range of stakeholders. This led to the second version of the SHEILA framework²³, which consists of a list of 49 action points, 69 challenges, and 63 policy questions. (Please see appendix on page 35 for the full framework.)

The SHEILA framework can be used iteratively to guide the development of institutional policies and strategic planning for LA. We tested and validated it through six workshops between March and November 2018, involving 200 participants from across the world. The participants came from organisations including higher education, government organisation, not-for-profit organisation, and technology industry. Based on the feedback, we further developed the SHEILA framework into an interactive, web-based tool, which allows users to customise a policy framework based on their institutional contexts and needs. The latest development of the tool is accessible here: <http://sheilaproject.eu/sheila-framework/>

²²http://bit.ly/SHEILA_framework_v1

²³http://bit.ly/SHEILA_Framework_v2

4.4.3 THE FOUR ADOPTION CASES

Thus far, the SHEILA framework has been used to assist with the adoption of LA in four European HEIs – the University of Edinburgh, Universidad Carlos III de Madrid, the Open University of the Netherlands, and Tallinn University.

At the University of Edinburgh, the local policy development was supported by research evidence drawn from the SHEILA framework. Currently, the University adopts LA under the governance of a comprehensive policy – “Policy and Procedures for Developing and Managing Learning Analytics Activities”.²⁴ The adoption experience at the University of Edinburgh has also contributed to the SHEILA framework as one of the 51 institutional cases. One example of this mutual support is the connection between the policy prompt “will learning analytics be used as a management tool to monitor students or staff” in the SHEILA framework (Dimension 4 – Develop Engagement Strategy) and the University of Edinburgh’s LA policy principles²⁵, Principle 7 – “Data generated from learning analytics will not be used to monitor staff performance, unless specifically authorised following additional consultation.”

Similarly, at Universidad Carlos III de Madrid, the SHEILA framework has informed the policy development processes, particularly to initiate dialogues among different stakeholders. In Spain, existing laws together with the European General Data Protection Regulation [14] strictly govern the use of personal data. Currently, the SHEILA framework serves as an additional reference to refine the local data processes and to shape an institutional strategy for LA, such as the approach to training for key stakeholders.

At the Open University of the Netherlands, the SHEILA framework has also helped facilitating conversations among key stakeholders to consider the consequences of LA and the need to govern the process with a sound policy. In addition, the SHEILA framework was used to gauge the readiness of teaching staff and students for LA.

At Tallinn University, the SHEILA framework has been used to assess the quality of existing initiatives of LA to reposition the institutional strategy for the integration of LA into teacher education (research-based teacher education and teacher-led inquiries) and existing practices at Student Affairs in identifying at-risk students. In particular, the SHEILA framework surfaced a challenge at the institution on the management level; that is, LA had to compete with other initiatives. Currently, the management team adopts the SHEILA framework to inform the development of a policy that can effectively govern the use of data for LA, both within the University and among other partner institutions and schools. A fruitful outcome of using the SHEILA framework is that the university has successfully opened a discussion with the Ministry of Education and Science to develop jointly strategy using educational data to support Estonian educational system in different levels and areas.

²⁴http://bit.ly/LA_policy_UoE

²⁵http://bit.ly/LA_policy_principles_UoE

5. Conclusion

The SHEILA project observed that the current state of adoption of LA among HEIs in Europe was still in early stages with few having a defined strategy or monitoring framework.

However, several institutions indicated an observation of short-term victories, such as experience-gain, cultural change, infrastructural upgrade, and a better understanding of legal and ethical implications since they started exploring LA.

This aligns with the observation of the key challenges that confronted HEIs in the deployment of LA, such as analytics expertise, data culture, staff buy-in, and technological infrastructure. Our findings also suggest that both teaching staff and students had strong interests in using LA to address existing challenges in learning and teaching. However, several concerns raised by these stakeholders would need to be addressed strategically so as to move towards wider and sustainable implementation of LA.

We therefore highlight four important areas of work:

1. Tool development
2. Policy development
3. User-centred implementation
4. Communication with primary stakeholders

First of all, a LA tool needs to increase teaching efficiency in addition to effectiveness, so as to increase buy-in from teaching staff. This means the tool has to be easy to operate, quick to present information that is easily understandable, and should save staff time as they go about their daily practices. Secondly, a sound policy needs to be in place to guide the use of LA, especially to address ethics and privacy issues, such as data access, security, and anonymity, which have been consistently raised as top concerns. Thirdly, the implementation of LA needs to respect the agency of both students and teaching staff, especially when it comes to receiving and offering interventions. While learning analytics may be capable

of identifying at-risk students, not every student would appreciate interventions to be undertaken, nor does every teacher have the capacity or see the need to undertake such procedures. It is also important to equip key users with data literacy and reflective skills to move from data to action. Finally, given that learning analytics is susceptible to ethics and privacy issues, a dialogic approach to LA can ensure that these issues are mitigated by incorporating the views of different stakeholders to develop a common vision and a sense of ownership over LA initiatives. It is also important to note that the value of LA has to be clarified within its limitations, so as to manage user expectations properly.

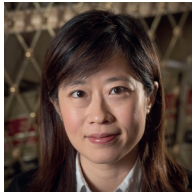
The key output of the project – the SHEILA framework – can support the four identified areas mentioned above by guiding institutions to consider key actions, challenges, and addressing them in policy and strategy processes. The adoption experience of the SHEILA framework at the University of Edinburgh, Universidad Carlos III de Madrid, the Open University of the Netherlands, and Tallinn University has also highlighted the human-centred feature of the SHEILA framework. The use of the framework and how it was developed are showcased in a MOOC²⁶ developed by the SHEILA project team to equip policy makers and institutional leaders with an understanding of LA and the skills to develop a sound policy and effective strategy to enable systematic adoption of LA in higher education.

²⁶<http://bit.ly/SHEILAMOOC>

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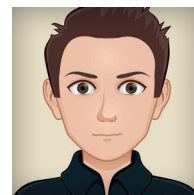
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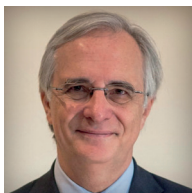
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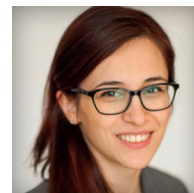
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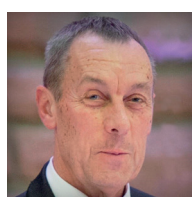
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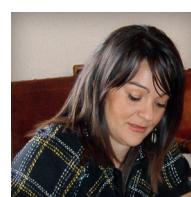
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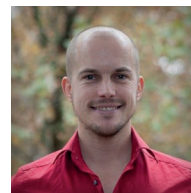
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Appendix

SHEILA framework v2

The second version framework updates the previous version that was released in July 2017 based on interviews with institutional leaders.

The second version framework updates the previous version that was released in July 2017 based on interviews with institutional leaders. This framework is informed by results of a group concept mapping activity with 29 international learning analytics experts, 18 student focus groups from four European institutions (n=74) and 16 staff focus groups from the same institutions (n = 59). Three key elements are included in this framework, including action, challenges, and policy.

- Action: strategic action points to take in each step of the ROMA framework. Items are grouped under themes, which are organised alphabetically – culture, ethics & privacy, financial & human resources, infrastructure, internal & external support, methodology, purpose, and stakeholder engagement,
- Challenges: potential challenges that exist in each step of the ROMA framework. These challenges are grouped by themes in an alphabetical order – capabilities, culture, ethics & privacy, infrastructure, management, methodology.
- Policy: questions to guide the development of a policy that addresses the listed action points and challenges. These questions are grouped by themes in an alphabetical order – data management, methodology, policy management, purpose, and stakeholder engagement.

Dimension 1: Map political context

Action	Challenges	Policy
Methodology <ul style="list-style-type: none"> Consider contextual elements (e.g., institutional size, structure) to identify opportunities for learning analytics. Identify opportunities to build learning analytics upon existing projects or practice. Purpose <ul style="list-style-type: none"> Identify internal and external drivers for learning analytics (e.g., problems to solve or areas to enhance). Identify the university's learning and teaching strategies. 	Infrastructure <ul style="list-style-type: none"> Existing solutions in the market mainly focus on addressing retention problems. There is no one-size-fits-all model, even within one institution (different disciplines and learning modes). Management <ul style="list-style-type: none"> Learning analytics competes with other institutional priorities. Methodology <ul style="list-style-type: none"> Institutions feel pressured to adopt learning analytics even though the needs for it are unclear. Wrongly assume that learning analytics can solve all problems without having identified key questions to answer (data driven approach). Learning analytics does not generate new insights into the understanding of learning or teaching. 	Purpose <ul style="list-style-type: none"> What are the reasons for adopting learning analytics (e.g., to improve teaching and learning)? Which problems are to be addressed by using LA? How do institutional objectives align with personal benefits for teaching staff and students?

Dimension 2: Identify key stakeholders

Action	Challenges	Policy
Stakeholder engagement <ul style="list-style-type: none"> Identify primary users of learning analytics (e.g., students, teaching staff, and senior managers). Identify senior management team (e.g., vice-chancellors, principals, provosts). Identify professional teams (e.g., IT, legal team, strategy team, Student Support, Student Registry, library). Identify academic teams (e.g. Learning & Teaching committee, Digital Learning Committee, research project teams) Identify external partners (e.g., researchers and service providers) Identify internal advocates of learning analytics among members of faculties (bottom-up approach). Identify required expertise (e.g., learning analytics expertise, IT expertise, statistical expertise, educational expertise, psychological expertise) 	Ethics and privacy <ul style="list-style-type: none"> Risk marginalising hard-to-reach students by drawing a distinction between students who opt out and those who opt into a learning analytics service. The choice of opt-out or not opt-in could affect those who choose to opt in regarding the quality of data and services provided. Data sharing (particularly with external parties) requires a careful check of security issues and breaches of privacy. Management <ul style="list-style-type: none"> Define ownership and responsibilities among diverse professional groups within the university. 	Data management <ul style="list-style-type: none"> How will consent be obtained and when? What are the circumstances where obtaining further consent is necessary? Is there an option to opt-out of (or opt into) any data collection and analysis? When will the option be available? Will students have a free choice of whether or not to accept interventions based on analytics? Who can access data? Who owns data? How will anonymity policy be applied to the processing and presentation of data? Can collected data be edited or deleted upon request? Will data be shared with researchers? Will data be shared with external parties? Is it justifiable? Who is the data controller? Methodology <ul style="list-style-type: none"> Whose data will be collected? Stakeholder engagement <ul style="list-style-type: none"> Who is the policy for? Whose working activities will the policy shape? How will responsibilities be defined for each stakeholder? Will learning analytics exclude certain groups of students? Will there be mechanisms to address inequality? Will the policy cover those who choose to opt out (or not to opt into) a learning analytics service? How will the current policy be communicated to different stakeholders?

Dimension 3: Identify desired behaviour changes

Action	Challenges	Policy
<p>Purpose</p> <ul style="list-style-type: none"> Identify expected 'changes' to the current context and key stakeholders (e.g., teaching staff and students). Identify areas where different stakeholders will be supported by learning analytics (macro level – institution, meso level – department/programme, and micro level – teaching staff and students). <p>Stakeholder engagement</p> <ul style="list-style-type: none"> Consider responsibilities and implications for all stakeholders Mind inadvertent consequences and make sure the benefits of learning analytics to students outweigh risks. 	<p>Capabilities</p> <ul style="list-style-type: none"> Immature skills of interpreting data lead to wrong decisions. <p>Ethics and privacy</p> <ul style="list-style-type: none"> People mistrust the result of an analysis if the process is not transparent or if the analytical model is too complicated to understand. Unethical profiling of students may occur when selecting those that are more likely to succeed. <p>Infrastructure</p> <ul style="list-style-type: none"> Learning analytics can reveal what was/is happening and predict what is likely to happen, but it may not explain the observed phenomenon or provide a direct solution. <p>Management</p> <ul style="list-style-type: none"> Students may be prone to choose subjects where they are likely to perform well. Users may game a LA system. Those who need support may not necessarily make use of information from learning analytics. <p>Methodology</p> <ul style="list-style-type: none"> An experimental approach is susceptible to a sense of uncertainty about the return on investment. 	<p>Methodology</p> <ul style="list-style-type: none"> How will transparency be achieved throughout a project cycle (data collection, analysis, and usage)? <p>Purpose</p> <ul style="list-style-type: none"> What positive changes will learning analytics bring to the current situation (e.g., learning and teaching landscapes)? Why are these changes important to us? <p>Stakeholder engagement</p> <ul style="list-style-type: none"> What are the mechanisms to deal with inadvertent consequences? Who will benefit from learning analytics? How will the purpose and functions of learning analytics be communicated to primary users?

Dimension 4: Develop engagement strategy (*tends to iterate with Dimension 5)

Action	Challenges	Policy
<p>Ethics and privacy</p> <ul style="list-style-type: none"> Consult relevant policies and codes of practice (e.g., Jisc's Code of Practice for Learning Analytics, and data protection policies) Consider establishing an ethics committee. <p>Financial and human resources</p> <ul style="list-style-type: none"> Seek funding. Appoint specialists to lead learning analytics projects. Establish a diverse working group (including teaching staff and students) and define a clear leadership structure. <p>Internal and external support</p> <ul style="list-style-type: none"> Align learning analytics with the wider institutional strategies or introduce learning analytics into the university's strategy. Embrace the whole system with guidance from key leadership. Engage with research projects locally or through collaboration with other institutions. <p>Methodology</p> <ul style="list-style-type: none"> Engage with existing LA cases and literature. Consider phases of implementation (e.g., explore data, carry out pilot projects, seek feedback from users, and develop a policy for the adoption of learning analytics). Decide the scope of the project – the range of data. Choose analytical models and define metrics. Select data that will be fed back to different stakeholders. Consider providing a safe environment (e.g., a sandbox) for testing or research purposes. Decide forms of interventions (e.g., automatic systems, personal contacts, learning resources). 	<p>Ethics and privacy</p> <ul style="list-style-type: none"> Learning analytics may induce fear and discomfort about surveillance. Surveillance leads to conscious or unconscious behavioural alteration that is against the goals of learning analytics. It is arguable to base predictive models on pre-determined factors, such as demographic characteristics. Predictive models may result in unequal access to learning or support resources among students. Learning analytics profile students and provide unequal support as a result (e.g., focus on struggling students and ignore others). Learning analytics removing student agency from them by drawing attention away from their own responsibility for learning. There are conflicts between good intentions to support students and unintentional intrusion into privacy. <p>Management</p> <ul style="list-style-type: none"> Overloading primary users with too many messages about analytics results. Strict data protection laws could restrict the way learning analytics is operated. Disengaged students remain hard to reach. <p>Methodology</p> <ul style="list-style-type: none"> Over rely on data and fail to consider the experience and knowledge of instructor/tutors about students and course designs. Feedback is provided without proper support, which leaves students in anxiety or complacency, thereby demotivating them. Focus on identifying students at risk and overlook the pedagogical design of curriculum or learning support. Peer comparison may demotivate students. Unsuccessful students may be discouraged by warning messages. Learning analytics is used as a metric to judge students and teachers rather than evidence to support learning and teaching. 	<p>Methodology</p> <ul style="list-style-type: none"> What kinds of data will be collected to achieve the identified objectives? When will data be collected? What is the scope of data collection? What are the methods of data collection? What kinds of data will be presented? How? To whom? How will the results of analytics be interpreted within the context? What kinds of expertise needs to be involved in this process? Does it include teaching staff and students? How will the results of analytics be communicated in a way that motivates learning? How will resources be distributed efficiently and fairly as a result of the analysis of data? Will there be interventions based on analytics? What are the circumstances? Will learning support and resources be made available to all students or only targeted students? Who will decide the forms of interventions and triggers? How will interventions take place? Who will be affected by the interventions? Who will oversee ethical conducts related to learning analytics? How will students' responsibility for learning be highlighted and considered in the design and implementation of learning analytics? <p>Purpose</p> <ul style="list-style-type: none"> What are the objectives for learning analytics? How do they align with the institution's vision for education? Will learning analytics be used as a management tool to monitor students or staff? Will learning analytics be used as a deficit model targeted at supporting students at risk of failure?

Dimension 4: Develop engagement strategy (continued)

Action	Challenges	Policy
Stakeholder engagement <ul style="list-style-type: none"> • Raise awareness and understanding of learning analytics among teaching staff and students through publicity and meetings/ workshops/ conferences. • Discourage teaching staff and students from gaming the system. • Establish communication channels between different stakeholders across the institution. • Consider the best ways to present analytics results (e.g., visualisation). • Provide training for users (e.g., how to operate the tools, how to interpret data, how to transfer data into action). • Provide opportunities for students to feedback on results of analytics. • Invite teaching staff to contribute their professional knowledge to the design and implementation of learning analytics (e.g., guide students to reflect on possible ways to act on the results of analytics). 		

Dimension 5: Analyse internal capacity to effect change

Action	Challenges	Policy
<p>Culture</p> <ul style="list-style-type: none"> Evaluate institutional culture (e.g., trust in data and openness to changes and innovation). <p>Ethics and privacy</p> <ul style="list-style-type: none"> Evaluate existing legal framework and its applicability for learning analytics. <p>Financial and human resources</p> <ul style="list-style-type: none"> Evaluate financial capacity. Evaluate human capacity (e.g., data literacy, relevant expertise, staff workload, opportunities for skill transfer). <p>Infrastructure</p> <ul style="list-style-type: none"> Evaluate technological infrastructure. Evaluate resources available for primary users to uptake learning analytics (e.g., access to digital devices). <p>Methodology</p> <ul style="list-style-type: none"> Establish indicators of data quality and system efficacy Evaluate risks. 	<p>Capabilities</p> <ul style="list-style-type: none"> The maturity of data literacy varies among stakeholders and faculties. The lack of critical self-reflection skills reduces the chance to benefit from learning analytics. The understanding/ interpretation of data protection regulations vary among legal officers, researchers, and teaching staff. Digital capabilities affect the desire to opt into a learning analytics service. Limited awareness or discussion regarding privacy and ethical issues cripple the adoption of learning analytics when issues arise. The difficulty of comprehending algorithms leads to disengagement with or distrust of learning analytics among primary stakeholders. Results of analytics are interpreted and communicated by people without proper understanding of data (e.g., fail to contextualise data or interpret it with sufficient statistical knowledge). <p>Culture</p> <ul style="list-style-type: none"> Institution-wide buy-in is hard to reach. Instructors are more interested in establishing a research profile than enhancing teaching and learning. Senior managers are more interested in financial benefits to the institution than the benefits in enhancing learning and teaching. There is unequal engagement/ interest in learning analytics among primary users (e.g., differences in gender, age, and disciplines influence the degree of interest). There is no common understanding of learning analytics among stakeholders at different levels (e.g., managers, teaching staff, IT officers, and students). Concerns about data protection hinder buy-in. Reluctance to change is present among some teaching staff (e.g., try new or unfamiliar technologies, or change teaching styles). Training could be difficult to deliver when staff lack time. 	<p>Data management</p> <ul style="list-style-type: none"> How will data be stored and disposed? How often will the efficiency and security of existing data infrastructure be evaluated? <p>Methodology</p> <ul style="list-style-type: none"> How will data integrity be achieved? Is there an application procedure for using learning analytics for research or teaching purposes? Are the procedures different? <p>Policy management</p> <ul style="list-style-type: none"> Are there related policies in the university that the policy sits alongside/above/below? Are there any national/international policies that this policy has to adhere to? <p>Stakeholder engagement</p> <ul style="list-style-type: none"> What training will be deployed to scale up data literacy and incorporate learning analytics into daily practice? Will the training be compulsory for any stakeholder? What communication channels or feedback mechanisms will be in place? How will the implementation address the problem of time poor among teaching staff? Will the design of selected learning analytics tools address teaching and learning needs?

Dimension 5: Analyse internal capacity to effect change (continued)

Action	Challenges	Policy
	<p>Culture (continued)</p> <ul style="list-style-type: none"> Teaching staff perceive learning analytics as a burden rather than a tool to improve efficiency and efficacy of teaching (e.g., pressure on time, pressure on providing personalised support to a large group of students, analytics tools are not intuitive or applicable to specific courses). <p>Infrastructure</p> <ul style="list-style-type: none"> Some useful data remains inaccessible. Data is held in silos. Data is fragmented. Data is noisy. Setting up a learning analytics environment is costly. <p>Management</p> <ul style="list-style-type: none"> 2018 GDPR requires changes in existing practice and system (e.g., coping with individual opt-outs). Central steering groups and individual project groups do not coordinate. Engaging students with institutional policies in an informed way. 	

Dimension 6: Establish monitoring and learning frameworks

Action	Challenges	Policy
Methodology <ul style="list-style-type: none"> Set up measurable milestones. Establish qualitative and quantitative indicators of success. Develop methods to triangulate analytics results. Stakeholder engagement <ul style="list-style-type: none"> Seek feedback from primary users through various channels. 	Culture <ul style="list-style-type: none"> Low participation of primary stakeholders in top-down consultations (e.g., survey and meetings). Management <ul style="list-style-type: none"> Manage expectations (e.g., deliverables and impact). Methodology <ul style="list-style-type: none"> It could be hard to isolate learning analytics from parallel projects that support the same goals (e.g., enhance learning and teaching) when measuring success. Fail to recognise and address limitations of data and analytics models (e.g., uncapturable factors of learning, ineffective metrics, existing bias, inaccuracy of predictions). Overly depend on data that is conveniently available to justify a learning phenomenon. Fail to contextualise data. Wrongly assume causal relationship between learning outcomes and interventions or engagement patterns. Interventions introduced to one course may have negative impact on student engagement in another course. Emphasise measuring output (learning or teaching performance) and overlook developing input (e.g., strategies, skill development) Overlook the differences between individuals in their learning or teaching approaches. Definitions of learning vary, which impacts the way data is collected, analysed, and interpreted. 	Methodology <ul style="list-style-type: none"> What defines success or failure? How will success be measured? What are success indicators? Who defines success measures? What expertise needs to be involved? When will evaluation take place? Who will carry out the evaluation of impact? What are the limitations of learning analytics (what is learning analytics not meant to do)? Will any access to data lead to stereotypes and biased results (e.g., marking exams or assignments biasedly)? Are there any measures to ensure that students are equipped with sufficient knowledge to make opt-in/out decisions? Policy management <ul style="list-style-type: none"> How often will the policy be reviewed and updated? Who will be responsible for the policy?

For the full version of the SHEILA framework v2, please visit:
http://bit.ly/SHEILA_Framework_v2

For the latest development of the web tool, please visit:
<http://sheilaproject.eu/sheila-framework/>



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